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Impact of optimised distributed energy resources on local grid constraints

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ABSTRACT

Optimisation models have been extensively used for finding optimal configuration and operation of distributed energy technologies. The main objective in most of these models is to find the optimal configuration of distributed energy technologies that will meet a certain energy demand with the least cost and emissions. Local grid constraints are not considered in the optimisation of distributed energy resources in most of these models. This implies that some optimal solutions from these models may not be possible to integrate due to a violation of steady state voltage and thermal limits which are important to Distribution Network Operators (DNO). In some cases, where a joint optimisation approach is utilised and local grid constraints are considered, it becomes computationally complex due to the nonlinear nature of Alternating Current (AC) power flow equations for electricity networks.

In this paper, the impact of optimised Distributed Energy Resources (DER) on a modelled microgrid was evaluated with an AC time series power flow using a soft-linking method. The soft-linking method avoids the computationally complex nature of joint optimisation methods. Different scenarios of the optimised DER were simulated and evaluated based on voltage excursions and energy losses. The results provide insights into the impact of local grid constraints on the adoption of different scenarios of optimised DER.

1. Introduction

In this paper, the term DER is often used interchangeably with Distributed Generation (DG) [1]. DER planning in energy systems is either discussed from the perspective of DNOs or utility customers. In Ref. [2], a framework for the integration of DGs into electricity distribution networks is presented. The research work in Ref. [3] describes a distribution network expansion strategy considering DGs using a heuristic search method for finding optimal DG schemes. An interactive fuzzy satisfying method for the optimal sizing and placement of DG units in distribution networks is proposed in Ref. [4].

In Ref. [5], a technique was developed to manage power flows in a microgrid with electric vehicles and DGs. The DNO perspective of managing DER is aimed at utilising DER to manage distribution network operation and defer network investments. In Ref. [6], an optimisation framework was proposed to manage DNO owned storage devices in order to maximise network asset utilisation. Reference [7] implemented an automatic grid upgrade algorithm for managing distribution network hosting capacity with DER. A control technique for DNO owned energy storage devices to manage peak demand on Low Voltage (LV) distribution network is presented in Ref. [8]. Reference [9] reviewed and analysed curtailment schemes for DNOs to minimise some of the challenges associated with providing access for DER in capacity constraint distribution networks. A hybrid genetic algorithm and optimal method for siting and sizing of DGs in a distribution network are presented in Ref. [10]. The method in Ref. [10] enables DNOs to optimally connect DGs from a potential number of adoption options.

In other studies, DGs are studied from the viewpoint of utility customers and large retail aggregators. For example, reference [11] presented an optimisation technique for the management of demand side and schedules of a small scale Photo Voltaic (PV) battery on behalf of the customer. Rising energy costs and the need to reduce emissions due to increase in energy demand is presenting a strong case for the adoption of DER technologies in the customer premises [12]. In Ref. [13] a Distributed Energy Resources Customer Adoption Model (DER-CAM) optimal investment model was

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Nomenclature

AC	Alternating Current
DER	Distributed Energy Resources
DG	Distributed Generation
DNO	Distribution Network Operator
HOMER	Hybrid Optimisation Model for Electric Renewables
LV	Low Voltage
MILP	Mixed Integer Linear Programming
O&M	Operation and Maintenance
PV	Photo Voltaic
OL	Overhead Line
SC	Service Connection
ToU	Time of Use
m	month: January–December
d	day-type: week, peak, weekend
h	hour: 1–24 (hourly timestep)
$P_{NET}(m,d,h)$	The net load (kW) on the node connecting the mid-rise apartment
$P_{DER\_ONSITE}(m,d,h)$	The total power (kW) produced by DER technologies
$P_{GRID}(m,d,h)$	The power (kW) imported from the grid
$P_{DEMAND}(m,d,h)$	The electricity demand (kW) of the mid-rise apartment

developed to analyse DER deployment options for a large retail shopping centre. Reference [14] developed an optimisation model to optimise feed in tariff revenue for customer owned PV system with battery storage. Hybrid Optimisation Model for Electric Renewables (HOMER) is an optimisation tool that finds the best microgrid configuration with least net present cost [15]. Reference [16] used HOMER to develop a method for finding optimal DER system configurations in regions with unreliable electricity from the grid. Reference [16] found that improved reliability increases cost but can be justified for customers requiring increased reliability. In Ref. [17], a hybrid system model was developed in HOMER to optimally generate electricity and heat using local DER in Ireland. The results in Ref. [17] indicate that the cost of energy for grid connected DER systems is generally higher than for standalone DER systems. A microgrid supplying an industrial area was sized using local DER in HOMER and the optimal microgrid operation was dynamically investigated in Ref. [18]. Initial simulation results in Ref. [18] show a good agreement between the HOMER model and the microgrid's dynamic model. DER-CAM is an optimisation model for evaluating adoption options for DER in microgrids [12]. DER-CAM is formulated as a Mixed Integer Linear Programming (MILP) tool. In Ref. [19] DER-CAM was enhanced to consider building retrofit measures along with investment options for the adoption of DER in building microgrids. Reference [20] enhanced DER-CAM's thermal energy storage model, the improved model indicates a better estimation of thermal energy storage losses.

Based on the literature reviewed, most models discussing the customer viewpoint do not consider network constraints (in terms of power flow) in their optimisation formulation. It was assumed that the distribution network can accommodate all operations and configurations of grid connected DER. According to [21] a joint optimisation formulation that considers both the DNO and customer perspective could be developed in DER planning. However, such a solution could be computationally expensive with no easy solution. This is due to the computational task of integrating nonlinear AC power flow equations in such optimisation models. Linearising these equations to include a DC power flow instead of AC power flow in the formulation of the model is a method of avoiding the computational task of including AC power flow constraints in such optimisation models. Examples of these linear programming based formulations for power system studies can be found in Refs. [22,23]. The application of DC power flow method in evaluating optimised DER can be seen in Ref. [21]. However, these simplifications may not show the real impact of optimised DER on electricity distribution network. This paper extends the concept of optimal investment decisions for the adoption of DER to consider local grid constraints while avoiding computationally complex joint optimisation approaches.

In this paper, a soft-linking method to evaluate the impact (in terms of voltage profiles and energy losses) of optimised DER on a modelled microgrid using a time series power flow is presented. The impact of the optimised DER on the voltage profiles and energy losses of the modelled network is analysed. The soft-linking method inherits the benefit of detailed optimisation models such as DER-CAM while adding a soft-linking approach for evaluating the impact of these solutions on local distribution network constraints. The soft-linking method is the main contribution of this paper. The soft-linking method is realised by simulating the optimised DER system schedules (with different investment scenarios) in a times series power flow and evaluating the impact of each scenario in terms of voltage profiles and energy losses. Two main case studies are developed for a mid-rise apartment. They correspond to finding optimal investment decisions for the adoption of DER in DER-CAM and the impact of their optimised schedules on a modelled microgrid. The rest of the paper is organised as follows. Section 2 briefly describes the DER-CAM optimisation model, its input data and the case studies considered. In Section 3, the soft-linking method developed in this paper is presented along with the modelled microgrid data and the load flow case studies considered. Discussions of the case study results considered in Sections 2 And 3 are provided in Sections 4 and 5 respectively. Conclusions drawn from this paper are provided in Section 6.

2. DER-CAM model

DER-CAM is a decision support tool for evaluating the economic merit of investing in DER for buildings and microgrids.

2.1. Optimisation formulation

Fig. 1 shows the optimisation modelling framework in DER-CAM. DER-CAM is formulated as a MILP model. The model considers energy demand, energy balance, DER technologies, and Time of Use (ToU) tariff data applicable to the building or microgrid.

An optimisation model of a mid-rise apartment is developed in DER-CAM using the site's energy demand data, electricity tariffs, demand charges and DER technology options. The focus of this paper is to develop a soft-linking method that evaluates the performance of optimised DER schedules in DER-CAM using time series power flow. A detailed description of the DER-CAM optimisation model formulation is presented in Ref. [24]. The high-level optimisation formulation (objective function and constraints) of DER-CAM is shown in Fig. 2. The model is simulated over the period of the optimisation index (m, h, d) described in the Nomenclature table.

DER-CAM simulates three typical load profiles (weekday, weekend and peak days), and solar insolation data for each month of the year. The model determines the optimal dispatch of deployed DER.

2.2. DER technologies in DER-CAM

Distributed energy technologies in DER-CAM are categorised as

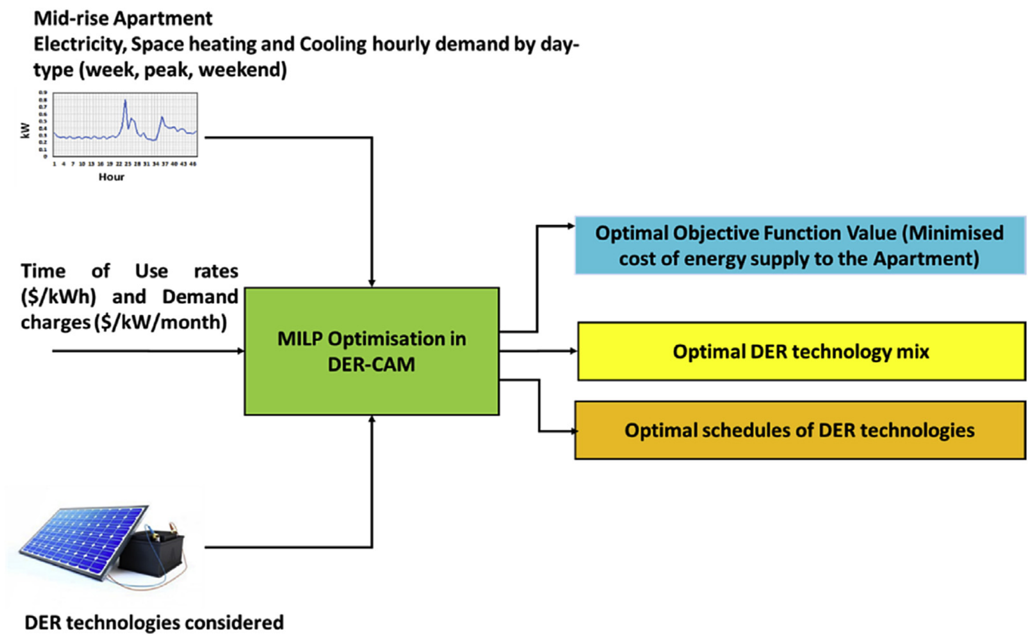

Fig. 1. DER-CAM optimisation framework.

```
MINIMIZE
   Annual energy cost:
     energy purchase cost
     + amortized DER technology capital cost
     + annual O&M cost
SUBJECT TO
   Energy balance:
     - Energy purchased + energy generated exceeds demand
   Operational constraints:
     - Generators, chillers, etc. must operate within
       installed limits
     - Heat recovered is limited by generated waste heat
   Regulatory constraints:
     - Minimum efficiency requirements
     - Maximum emission limits
   Investment constraints:
     - Payback period is constrained
   Storage constraints:
     - Electricity stored is limited by battery size
     - Heat storage is limited by reservoir size
```

Fig. 2. High-level optimisation formulation illustration in DER-CAM [12].

continuous technologies or discrete technologies. The continuous technologies such as stationary battery storage, solar PV and air source heat pump are modelled with a continuous variable in DER-CAM. Discrete technology includes diesel generators, fuel cells, microturbine and reciprocating engines. Only continuous technologies are considered for the mid-rise apartment studied in this paper.

2.3. Key assumptions of the DER-CAM optimisation model

The investment scenarios simulated in this study assume fixed energy prices over the period of investment. All DER equipment considered in the DER-CAM version used is assumed to be reliable, which means no maintenance or fault interruptions during scheduled operation periods that would otherwise affect the impact of demand charges on operating schedules.

The electricity demand data for the mid-rise apartment is obtained from the database in Ref. [25] which averages historical data of different building types into the DER-CAM format. The DER-CAM format models three typical day-types for each month of the year: week, peak and weekend days. The energy demand data is assumed to be deterministic in the investment version of DER-CAM. That means no changes in energy demand within the lifespan of the DER investment. This will otherwise affect the optimal operating schedules if uncertainties in demand were considered in the model.

A monthly fixed access fee to the grid is assumed for the mid-rise apartment. The monthly fixed fee for electricity in this case study is $ 118.28 and $ 64.48 for natural gas [26].

The solar insolation profile (kW/m^2) for the mid-rise apartment's location is a typical meteorological year historical data from Ref. [27] and averaged into DER-CAM format [25]. The DER-CAM format averages the historical data into one daily solar insolation (24 h) for each month of the year. All the other days of the same month are assumed to have the same solar insolation profile.

Maximum area allowed for solar PV investment was constrained to 700 m^2. Maximum payback of the DER investment scenarios was constraint to 10 years and the interest rate to 5%. In scenarios where PV generation is exported to the grid, the PV generation is sold using the default net-metering power exchange prices found in Ref. [25].

Load shifting is a form of energy management strategy in DER-CAM. The total energy remains unchanged when the load shifting strategy is applied. It consists of electricity load of each day-type that can be shifted, load increase and reduction in any given hour. It is assumed that no costs are associated with the load shifting strategy, which implies a high tendency to shift demand from periods of high ToU rates to lower rates. Thus, load shifting flattens the load profiles which minimises demand charges and energy purchase costs.

2.4. Input data

The datasets used for the case studies in this research is for a mid-rise apartment building. The mid-rise apartment's electricity loads are highest in summer (represented by a typical load profile in July) and lowest in winter (represented by a typical load profile in January) as shown in Fig. 3. The DER-CAM input data are summarised as follows:

- Solar insolation (for each month of the year) in kW/m^2. Fig. 4 shows the monthly insolation data for the location of the mid-rise apartment. The highest insolation occurs in September when insolation is greater than 0.9 kW/m^2. The solar insolation data was obtained from Ref. [25].
- End-use hourly load profiles (for electricity, cooling, gas, hot water, and space heating). These data sets are defined over three day-types: weekdays, weekend days and peak days. The peak days represent outliers in the data set for each month of the year when energy demand is at the peak. The end-use energy demand profiles (electricity, heating and cooling) for the mid-rise apartment were obtained from Ref. [25]. The DER-CAM model and data can be accessed from Ref. [28]. Average energy demand (electricity, heating and cooling) are shown in Figs. 5–7. The electricity tariff data used in this study is the Pacific Gas and Electric E-19 tariff for medium/large buildings. The tariff data is available from Ref. [29].
- Electricity tariff and demand charges. The electricity tariff data used for simulating the mid-rise apartment in DER-CAM is made of energy charge ($/kWh) and demand charge ($/kW). The energy charge depends on the energy usage defined as ToU rates using three categories: peak, mid-peak and off-peak hours.
- Table 2 shows the ToU rates used for computing the electrical energy costs [29]. Demand charges represent a significant part of the energy bill in buildings with high electricity demand. Demand charges are based on the maximum demand observed within a specific control period. These control periods include peak, mid-peak and off-peak.
- Table 3 shows the power demand charges for each month of the year. The coincident hour refers to the hour when the electricity grid observes the global system peak and this hour is set monthly by the utility company [26].
- Capital costs, operation, and maintenance (O&M) costs for the distributed energy technologies considered in this study are based on the assumed values presented in Table 1.
- Interest rates on investments and maximum payback period.

The key cost assumptions of DER technology options are shown in Table 1. The installation and maintenance costs are based on the data obtained from Refs. [25,26].

The output data from the DER-CAM model shown in Fig. 1 includes the following:

- Investment decisions: optimal capacities of distributed energy technologies.
- Optimised dispatch of all distributed energy technologies adopted.
- Total minimised cost of energy supply (objective function).
- CO_2 emissions.

2.5. DER-CAM optimisation case study

Eight different scenarios were modelled in DER-CAM, each representing the adoption of different DER configuration that will minimise the cost of energy supply for the mid-rise apartment. Scenario 1 is a reference casestudy with no investment in DER and is used to evaluate the other seven scenarios where PV, battery storage, air source heat pump and load shifting strategy were considered. The combination of PV (with and without export allowed) with battery storage, air source heat pump and load shifting strategy is used to model the seven investment scenarios. Each scenario is described in Table 4. All power generated onsite in scenarios 2 to 5 was constrained to be consumed onsite, while in scenarios 6 to 8, the PV generation export is enabled to evaluate the impact of net power flows on the local distribution network.

3. Soft-linking method

The optimal investment decisions of DER-CAM to satisfy the energy demand requirements of the mid-rise apartment using optimised DER and the utility grid are tested on a distribution network model. This was simulated using a time series power flow in NEPLAN [30].

The method evaluates the impact of DER-CAM optimal decisions and dispatch schedules on voltage profiles and energy losses. The evaluation is carried out for the eight scenarios simulated in DER-CAM (see Table 4).

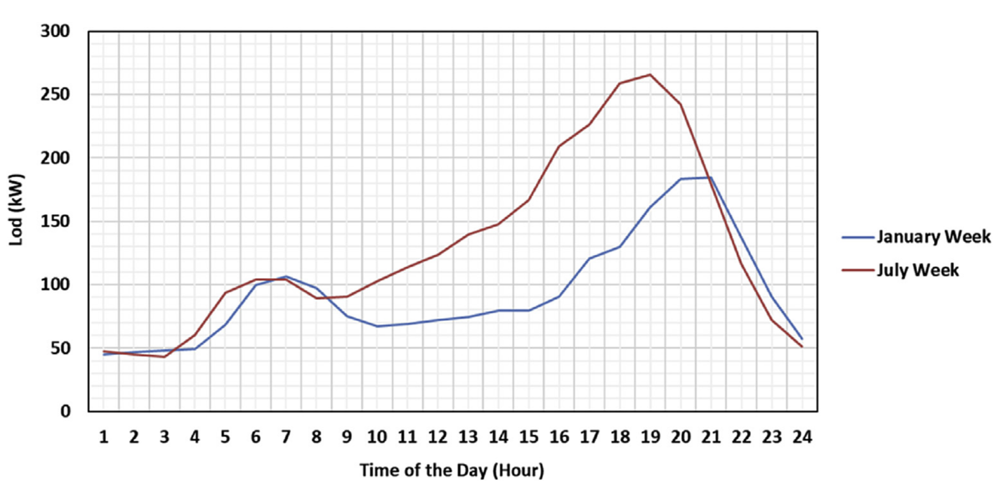

Fig. 3. Typical weekdays load profiles for the mid-rise apartment.

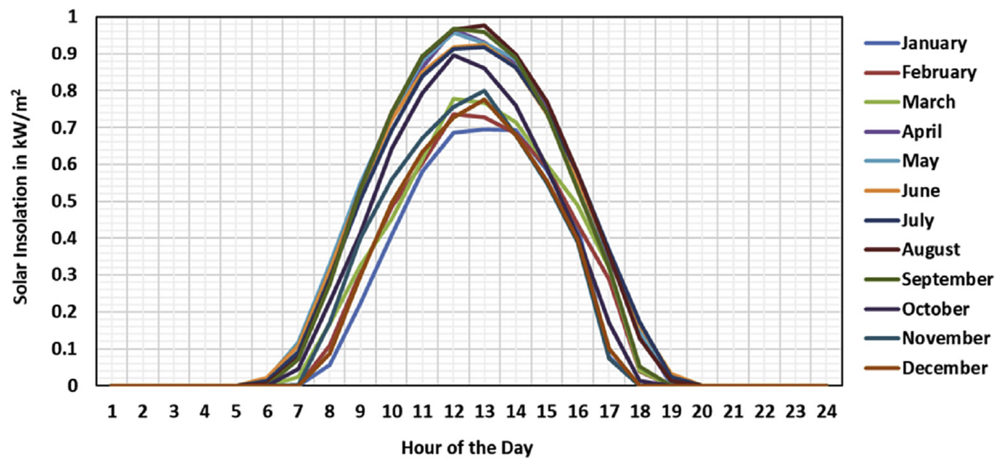

Fig. 4. Typical solar insolation for the mid-rise apartment's location.

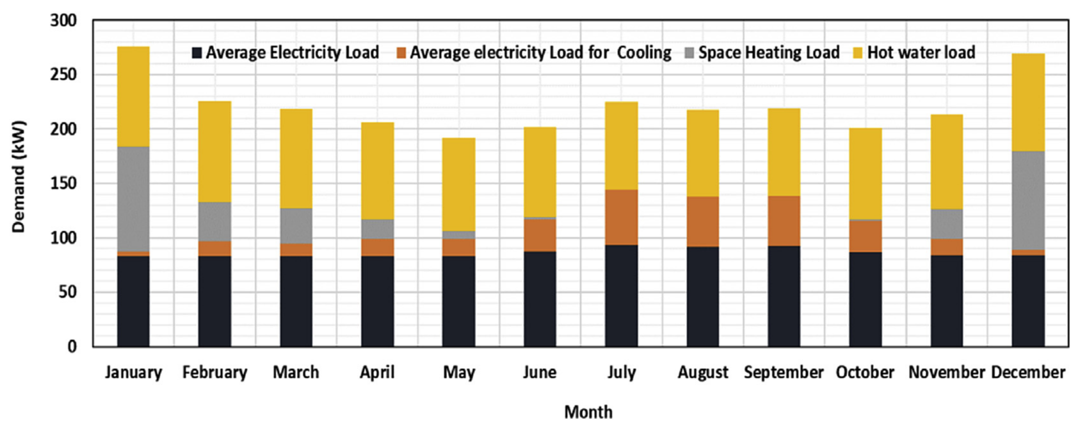

Fig. 5. Average demand for the mid-rise apartment over the weekdays.

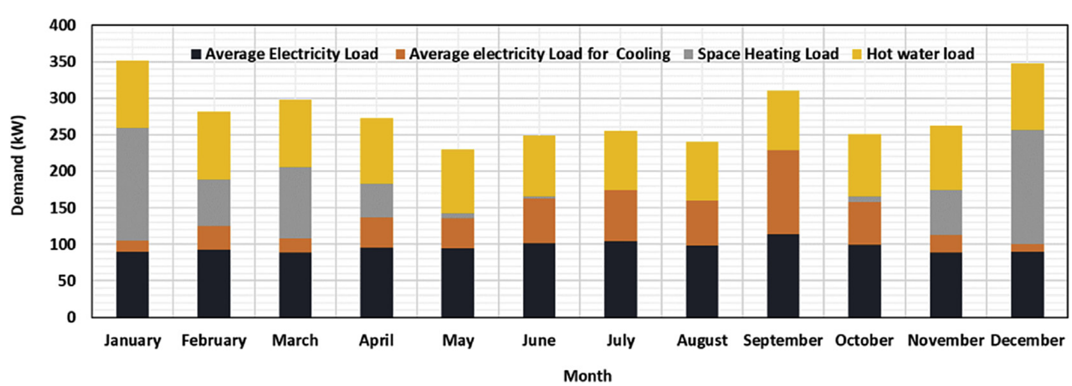

Fig. 6. Average demand for the mid-rise apartment over the peak days.

3.1. Description of the soft-linking method

The block diagram of the proposed soft-linking method is shown in Fig. 8. The soft-linking method consists of two parts, the DER-CAM part (described in Section 2) and the soft-linking part. The optimised output of DER-CAM (in terms of optimal schedules) are exported via a MATLAB script which computes the net power-flows for each scenario. This serves as an input to NEPLAN. NEPLAN runs a time series AC power flow based on the input from the MATLAB script.

3.2. AC load flow

The validity of the softlinking method is based on the following assumptions:

- The mid-rise apartment is connected to bus 9 of the microgrid benchmark model. The details of the benchmark microgrid model can be found in Refs. [31–33] (see Fig. 9).
- The microgrid benchmark model is assumed to be in a climatic condition similar to the mid-rise apartment where electricity

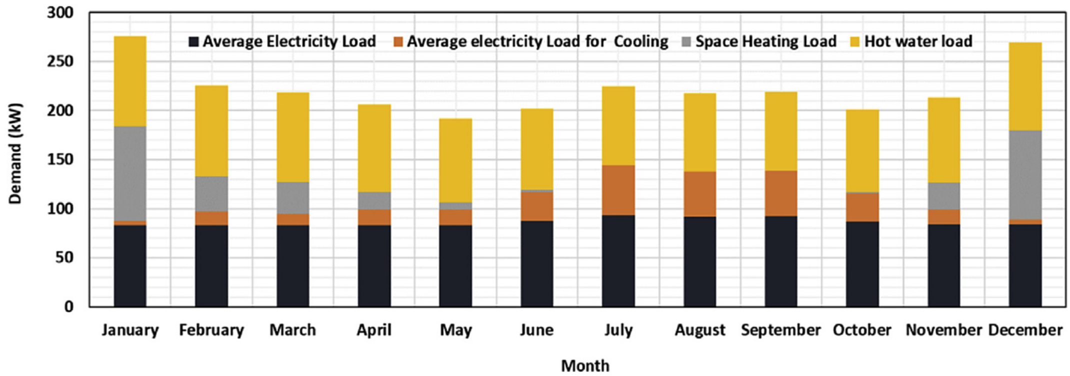

Fig. 7. Average demand for the mid-rise apartment over the weekend days.

Table 1
DER cost parameters options for DER-CAM case study.

DER technology	Installed cost ($/kW)	Installed cost ($/kWh)	Fixed O&M costs ($/kWh)	Lifespan (Years)
Solar PV	3350	–	0.25	30
Battery storage	–	700	–	8
Air source heat pump	754	–	0.52	10

Table 2
ToU rates [29].

Energy charge ($/kWh)	On Peak	Mid Peak	Off Peak
January	0	0.09451	0.07885
February	0	0.09451	0.07885
March	0	0.09451	0.07885
April	0	0.09451	0.07885
May	0.14026	0.09916	0.07512
June	0.14026	0.09916	0.07512
July	0.14026	0.09916	0.07512
August	0.14026	0.09916	0.07512
September	0.14026	0.09916	0.07512
October	0.14026	0.09916	0.07512
November	0	0.09451	0.07885
December	0	0.09451	0.07885

demand is maximum in the summer (due to additional cooling loads) and minimum in winter.

- The steady state voltage limits are based on [34]: ±10% of the nominal voltage between 0.9 p. u and 1.1 p. u.

The net power flows in bus 9 is computed using Equation (1) and iterated over all the eight scenarios described in Section 2.

$$P_{NET}(m,d,h) = \sum_{i}^{n} \left(P_{DER\_ONSITE}(m,d,h)\right) + P_{GRID}(m,d,h) - P_{DEMAND}(m,d,h) \quad (1)$$

A time series load flow with the net load profiles is then simulated in NEPLAN for each scenario. The results are written to a text file and analysed by plotting the voltage profiles and overall microgrid energy losses for all the scenarios computed in Equation (1).

The transformer and impedance data of the microgrid are obtained from Ref. [33] and presented in Tables 5 and 6 [33]. The microgrid is a 20/0.4 kV benchmark LV model. Fig. 9 shows the modelled microgrid and the node where the mid-rise apartment is connected.

The power flow simulations in NEPLAN are computed and evaluated for both voltage profiles of node 9 and energy losses for each scenario described in Section 2.

4. Optimisation results

For each run of the DER-CAM optimisation model, the minimised total cost of energy supply, total CO_2 emissions, and optimal dispatch strategy is obtained.

Table 3
Demand charges [29].

Demand Charge ($/kW)	Coincident	Non coincident	On Peak	Mid Peak	Off Peak
January	0	9.71	0	0.24	0
February	0	9.71	0	0.24	0
March	0	9.71	0	0.24	0
April	0	9.71	0	0.24	0
May	0	16.04	9.71	3.33	0
June	0	16.04	9.71	3.33	0
July	0	16.04	9.71	3.33	0
August	0	16.04	9.71	3.33	0
September	0	16.04	9.71	3.33	0
October	0	16.04	9.71	3.33	0
November	0	9.71	0	0.24	0
December	0	9.71	0	0.24	0

Table 4
Description of simulated scenarios in DER-CAM.

Scenarios	Description
Scenario 1 (S1)	Base case, all energy supplies and demand are met by the utility grid
Scenario 2 (S2)	Investment in solar PV (self-consumption) and Battery is considered
Scenario 3 (S3)	Investment in solar PV (self-consumption) and Battery with load shifting as a demand response strategy is considered
Scenario 4 (S4)	Investment in solar PV (self-consumption), Battery and Air Source Heat Pump considered
Scenario 5 (S5)	Investment in solar PV (self-consumption), Battery and Air Source Heat Pump. Load shifting as a demand response strategy is considered
Scenario 6 (S6)	Investment in solar PV (excess export) and Battery considered
Scenario 7 (S7)	Investment in solar PV (excess export), Battery and Air Source Heat Pump
Scenario 8 (S8)	Investment in solar PV (excess export enabled), Battery and Air Source Heat Pump. Load shifting as a demand response strategy is considered

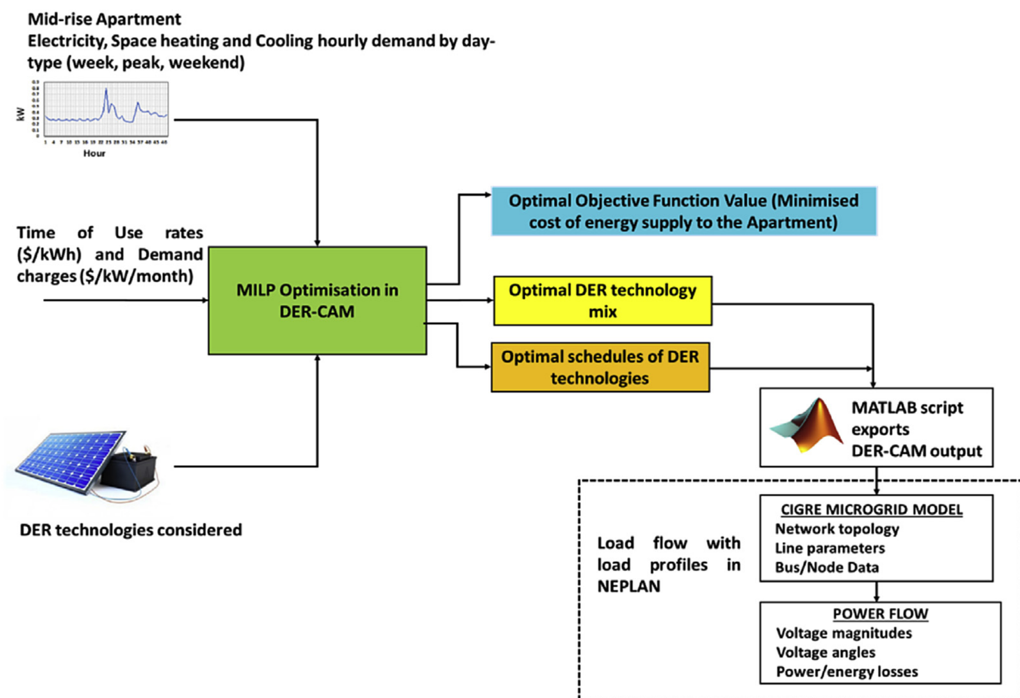

Fig. 8. Proposed soft-linking method.

4.1. Optimal investment decisions

A summary of the optimal DER configuration for each scenario is shown in Table 7. Relative to the reference scenario (scenario 1), scenario 8 achieves the highest savings (40.1%) while scenario 5 achieves the lowest CO_2 emissions.

4.2. Optimised dispatch schedules

With each optimal configuration in each scenario, an indicative dispatch strategy results for all three day-types and months of the year is obtained from DER-CAM. The detailed dispatch schedules for scenario 8 (the scenario with the highest savings for the mid-rise apartment) in winter (January) and summer (July) are shown in Figs. 11 and 13 respectively. Figs. 10 and 12 shows the winter and summer ToU rates ($/kWh) respectively and are used to explain the optimal dispatch strategies in Figs. 11 and 13. The dispatch schedules presented are for a typical weekday in winter and summer. The detailed dispatch schedules in all other months for scenario 8 are presented in Appendix A.

It could be seen in Fig. 11 that the electricity consumption of the air source heat pump is highest within the off-peak period (1:00–8:00) based on the ToU rate in Fig. 10. Fig. 11 shows that at the highest PV production between the hours (9:00–16:00), the grid electricity import goes to zero and the new load profile (thick black) line increases as the PV production varies and DER-CAM aims to maximise self-consumption. The battery state of charge (shown as a dashed line of the secondary axis of Fig. 11) rises to the maximum charging using an excess of PV generation and discharges at the peak winter ToU electricity rates (see Fig. 10).

It could be observed that there is no electricity load offset for cooling in the winter (represented by a typical weekday in January) for the mid-rise apartment. This is due to the low cooling demand in January.

However, in the summer the ToU tariff shown in Fig. 12 with on peak, mid-peak and off-peak is applied in the DER-CAM model. Fig. 13 shows the summer optimal dispatch schedules with high solar insolation, which implies high PV generation for self-consumption. Electricity consumption increases during the off-peak hours (1:00–8:00) see Fig. 12. This increase is showing the advantage of the load shifting strategy (see the thick black line in Fig. 13) and low tariff rates within that period.

It is also observed the increase of the cooling offset in the summer compared with the winter when there is no cooling load offset. This is due to the increase in the electricity demand for cooling by the mid-rise apartment during summer. The battery state of charge varies between the hours (8:00–13:00) representing charging (red area on the stacked graph in Fig. 13) and

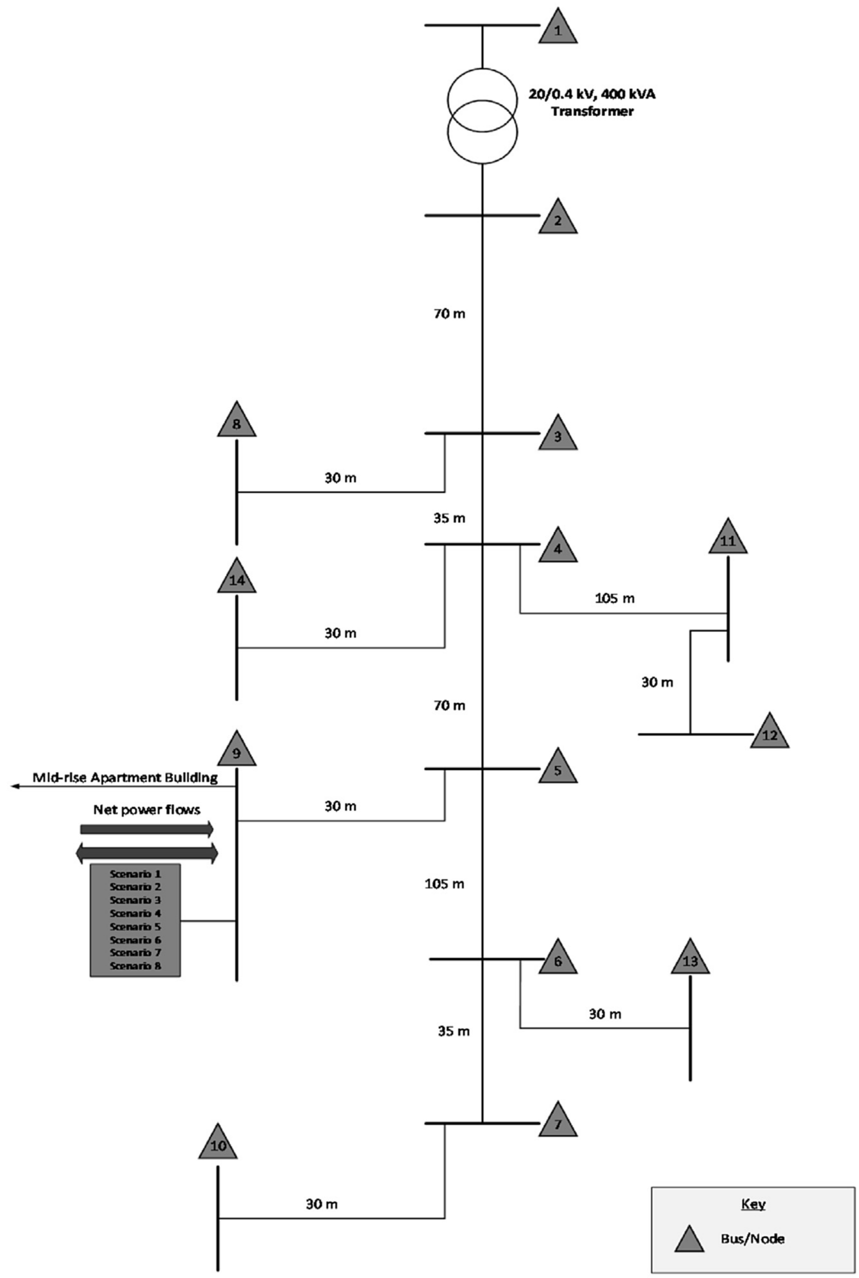

Fig. 9. Modelled microgrid network showing the connected mid-rise apartment.

Table 5
Transformer data [33].

Capacity (kVA)	Primary Side (kV)	Secondary Side (kV)	R (pu)	X (pu)
400	20	0.4	0.01	0.04

discharging (the light blue area on the stacked graph in Fig. 13). The discharging falls within the period of the high ToU rates and demand charges shown in Fig. 12 and Table 3 respectively. This decreases the energy supply cost within the periods of high demand charges and ToU rates.

5. Load flow results

The load flow is simulated over the optimisation index (m, h, d) shown in Equation (1). That is a period of 24 h for one typical day in each month of the year ($24 \times 12 = 288$ h for the complete year). The representation of hours in the year for all months is shown in Appendix B.

5.1. Voltage profiles

The load flow results are evaluated in terms of voltage profiles (weekdays, peak days and weekend days) for node 9 where the mid-rise apartment is connected and energy losses of the entire microgrid.

When discussing the results for typical weekdays, only the voltage profiles for scenarios 6 and 8 are presented. This is because scenario 1 and 6 have the most extreme voltage excursions in week day-types. In typical peak days, only the voltage profiles for

Table 6
Microgrid cable impedance [33].

Conductors	$Rph(\Omega/km)$	$Xph(\Omega/km)$	Lines
OL – Twisted cable $4 \times 120\ mm^2$ Al	0.284	0.083	(2-3), (3-4), (4-5), (5-6), (6-7)
OL – Twisted cable $3 \times 70\ mm^2$ Al + $54.6\ mm^2$ AAAC	0.497	0.086	(4-11)
SC – $4 \times 6\ mm^2$ Cu	3.690	0.094	(3-8), (6-13)
SC – $4 \times 16\ mm^2$ Cu	1.380	0.082	(4-14), (7-10)
SC – $4 \times 25\ mm^2$ Cu	0.871	0.081	(5-9)
SC – $3 \times 50\ mm^2$Cu Al + $35\ mm^2$ Cu	0.822	0.077	(11-2)

Table 7
Optimal investment decisions for each scenario.

Scenario	PV size (kW)	Battery Storage Size (kWh)	Battery Power (kW)	Air Source Heat Pump (kW)	PV Exports	Load Shifting	Total Annual Energy Costs (k$)	Total Annual CO_2 Emissions (kg CO_2 emissions)	Total Savings Percent
Base case (S1)	0	0	0	0	No	No	601.1	736600	–
S2	107	72	56.0	0	No	No	461.9	605900	23.9
S3	107	2	1.9	0	No	Yes	431.8	603000	28.9
S4	107	67	53.0	61	No	No	387.5	466800	36.2
S5	107	0	0	61	No	Yes	365.4	464700	39.8
S6	107	222	173	0	Yes	No	458.6	670900	24.5
S7	107	128	100	63	Yes	No	386.8	500500	36.3
S8	107	6	4.3	61	Yes	Yes	363.3	481200	40.1

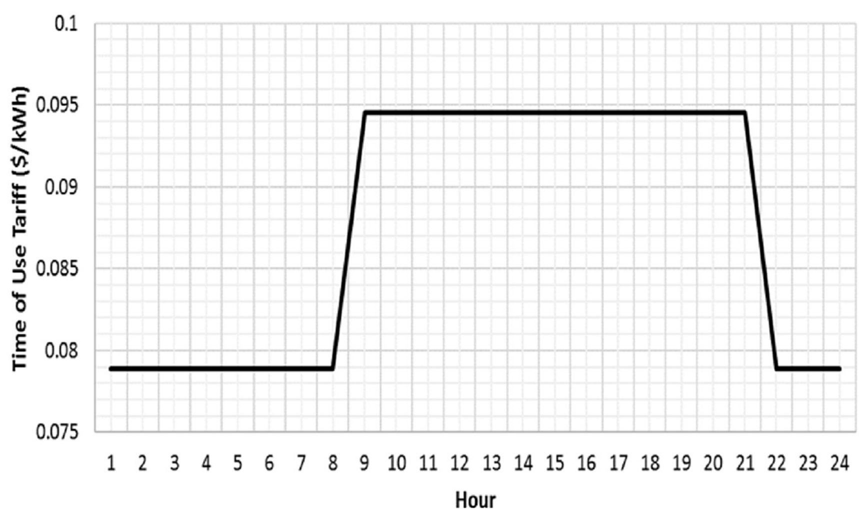

Fig. 10. Winter ToU tariff.

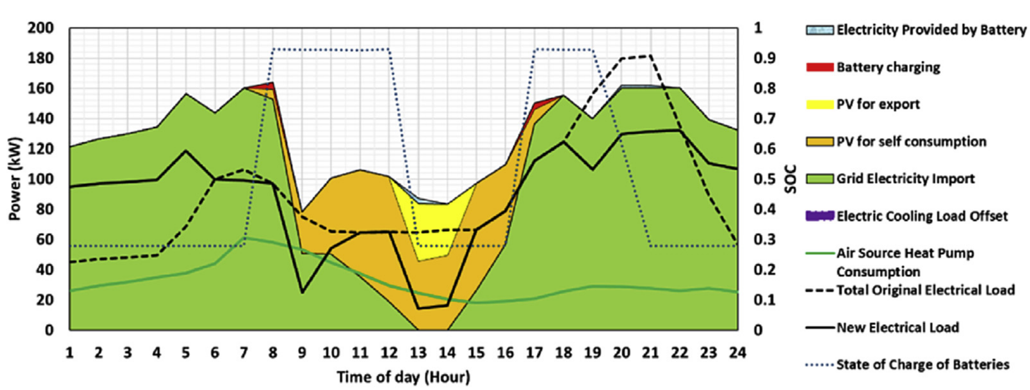

Fig. 11. Optimal Electricity Dispatch for a typical day in January (winter).

Fig. 12. Summer ToU tariffs.

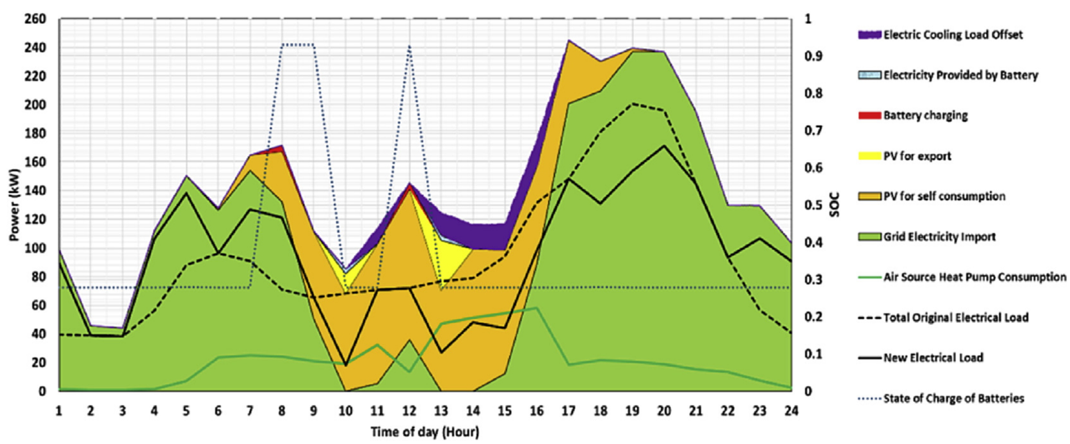

Fig. 13. Optimal Electricity Dispatch for a typical day in July (summer).

scenarios 1, 6, and 8 are presented. This is because scenario 1 within peak days had voltage excursions beyond the 10% lower limit. The voltage profiles for the typical weekend days are presented considering only scenarios 6 and 8. Scenario 6 has a small voltage excursion beyond the 10% lower limit. Scenario 8 (being the scenario with highest savings and lowest cost) is included in all the typical days (week, peak and weekends) to evaluate its impact on voltage profile of node 9.

The combined voltage profiles plot for all the scenarios are shown in Appendix C.

The peak days are outliers within the data set and occupancy level of the mid-rise apartment and energy demand is highest within this period compared with the weekdays and weekend days (see Fig. 6). Fig. 14 shows the voltage profiles for scenarios 6 and 8 in typical weekdays. It could be seen that the voltage drops for scenario 8 are within the ±10% limit except for scenario 6. The voltage excursion beyond the 10% lower limit in the case of scenario 6 occurs between hour 144 and 228. These hours correspond to the month of June and July (see Appendix B for hours with their corresponding months) where the highest demand for cooling occurs for the mid-rise apartment.

The voltage profile in scenario 8 which has the lowest cost and highest savings in terms of energy supply (see Table 7) are within the ±10% voltage limit. This is due to the optimal investment in an air source heat pump, battery storage, and load shifting strategy which minimises grid electricity import and high demand charges during the summer months.

As earlier observed the typical peak days are outliers in the energy demand data of the mid-rise apartment and therefore the large voltage deviations are seen in Fig. 15. This figure is presenting the voltage profiles for the typical outlier data sets in scenarios 1, 6 and 8.

It is interesting to note that the 10% lower limit is violated and p. u voltage drops from 0.9 p. u to about 0.83 p. u in case of scenario 1 (which represents the base case where no investment in DER is considered). The violations occur between the hours 204 and 216. These hours occur in September which is within the summer months in the dataset of the mid-rise apartment. This is due to the high cooling demand in the hours (11:00–16:00) (see Fig. 13). Scenario 6 and 8 slightly violates the 10% lower limit at 206 h, which represents a typical peak outlier with high electricity demand for cooling during the summer.

The weekend days represents a slightly higher occupancy levels compared with the typical weekdays for a residential building. Fig. 16 shows the voltage profiles at the node 9 where the mid-rise apartment is connected.

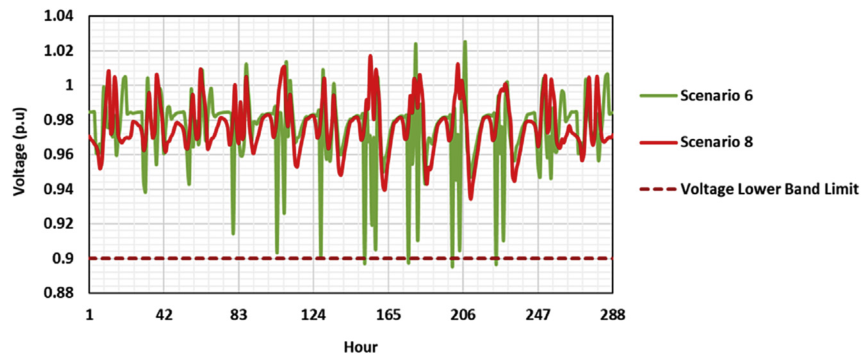

Fig. 14. Voltage profiles for typical weekdays.

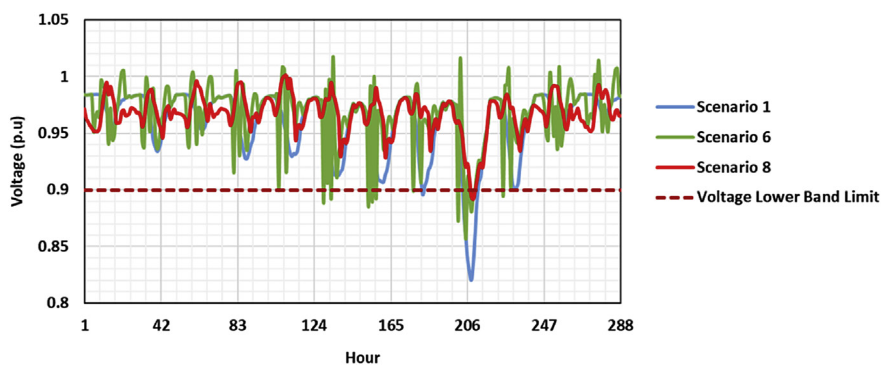

Fig. 15. Voltage profiles for typical peak days.

It is observed that only scenario 6 has voltage violation in hours 156 and 204, these hours represent 12 noon in July and September respectively. This is due to an increase in cooling demand and fluctuation in PV generation output. This scenario has a total optimised savings of 24.5% (see Table 7), and may not be an optimal alternative for investment, both in terms of the optimisation results and impact on voltage profiles (observed at node 9).

5.2. Energy losses

The total energy losses of the microgrid for each scenario are evaluated and shown in Fig. 17. The business as usual case (scenario 1, with no investment in DER) leads to the highest energy losses (about 2.76 MWh) compared with all other scenarios. Scenarios 2 and 3 achieve DER-CAM optimisation savings of 23.9% and 28.9% respectively compared with scenario 1. The lowest energy losses compared to other scenarios is achieved in scenarios 2 and 3 and these are 1.57 MWh and 1.58 MWh respectively.

Using DER-CAM optimisation model, the highest savings were achieved in scenario 8. This represents 0.48 MWh more energy losses comparing with scenarios 2 and 3 with the lowest energy losses. This shows that there may be some solutions obtained using distributed energy technologies planning optimisation models which are optimal from the viewpoint of the DER owners but not feasible from the local electricity network's technical constraints viewpoint.

6. Conclusions

In this paper, a soft-linking method for assessing the impact of

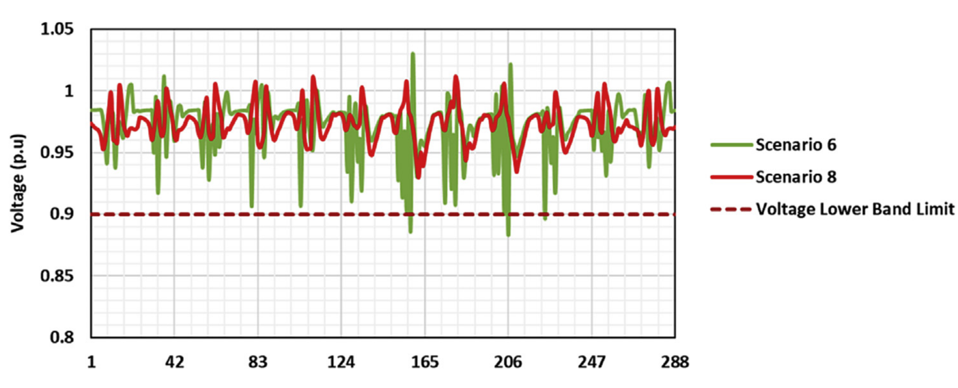

Fig. 16. Voltage profiles for typical weekend days.

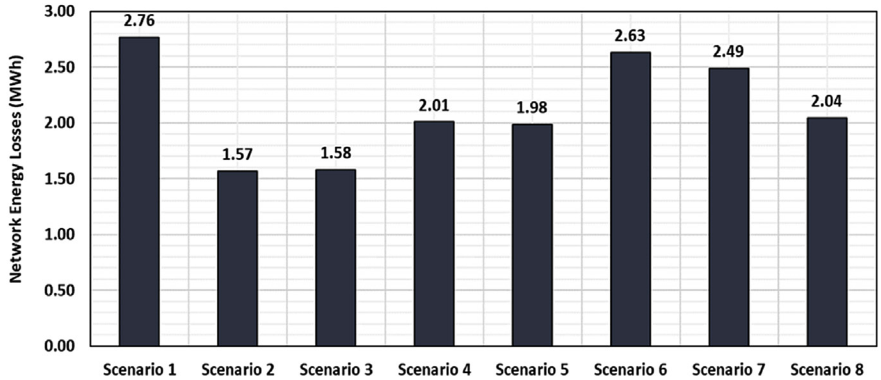

Fig. 17. Microgrid Energy losses.

optimal investment decisions from DER planning tools on local electricity networks was presented.

A DER investment planning model for a mid-rise apartment was developed in DER-CAM. The optimal investment decisions and schedules were interfaced (using a script written in MATLAB) to a time series load flow model. This avoids the computationally complex nature of joint optimisation approaches. The results demonstrate the potential of the soft-linking method in extending the capabilities of DER optimisation models by achieving savings for buildings/microgrids and identifying optimal solutions that will operate within the limit of the local electricity network constraints as seen in scenario 8. The main findings are summarised as follows:

- During typical peak days within the year, scenarios 1 and 6 violate the ±10% voltage lower limit (voltage drops from 0.9 p. u to about 0.83 p. u in the case of scenario 1), when compared to the weekdays and weekend days.
- The business as usual case with no investment in DER contributed to the highest overall microgrid energy loss of 2.76 MWh. This shows that optimal DER planning integrated with the soft-linking method can identify investment scenarios that will minimise energy losses on the local distribution grid.
- Not all optimal solutions obtained using distributed energy technologies planning optimisation models are feasible from the local electricity network's perspective in terms of voltage profiles and energy losses.
- The soft-linking method presented in this paper can be of benefit to an aggregator of buildings in a community looking to optimise investment decisions in low carbon technologies within their local distribution network constraints. It inherits the benefit of detailed optimisation models such as DER-CAM while adding a soft-linking approach of evaluating the impact of these solutions on distribution networks.

Acknowledgement

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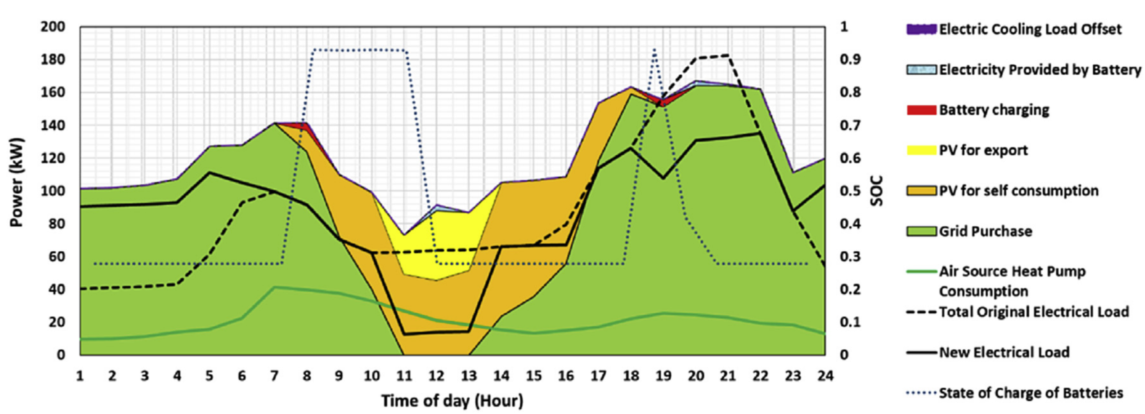
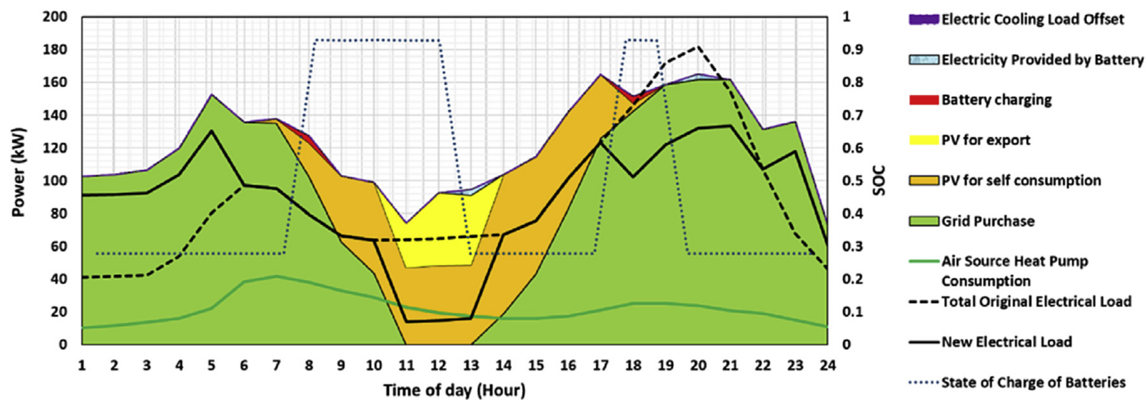
Appendix

Appendix A

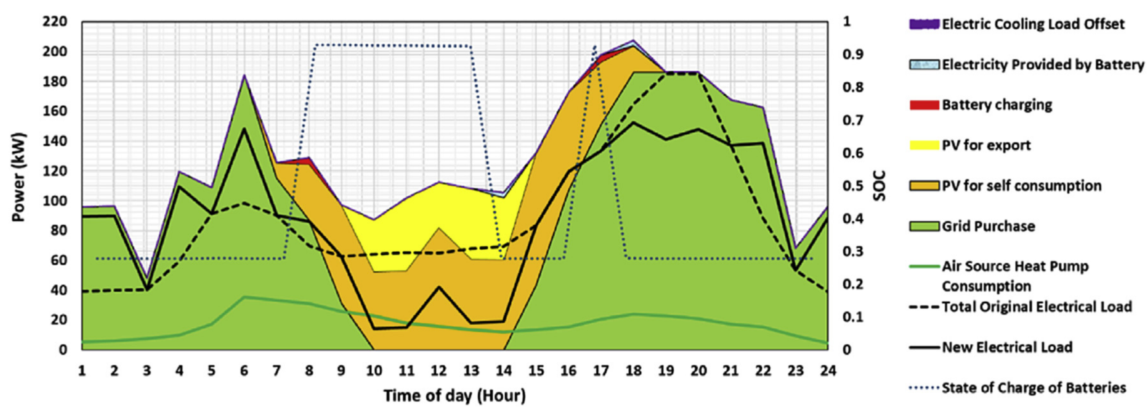
Scenario 8: February



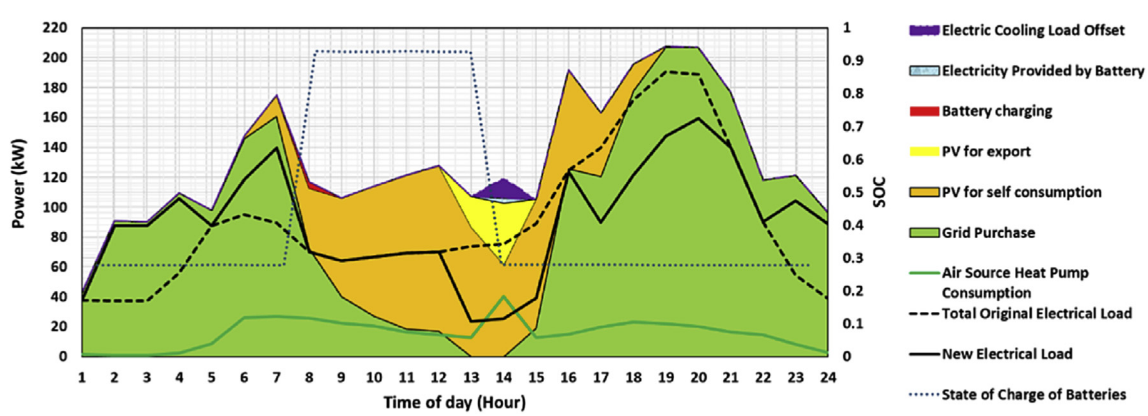
Scenario 8: March



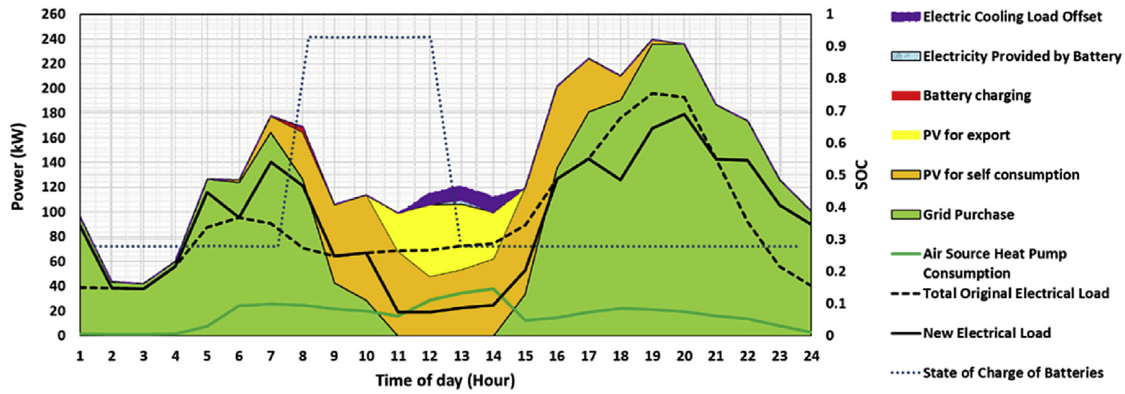
Scenario 8: April



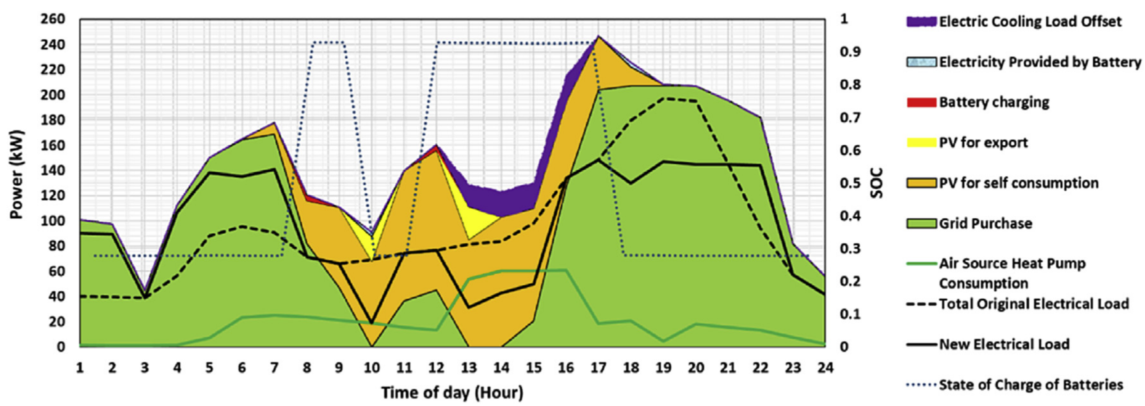
Scenario 8: May



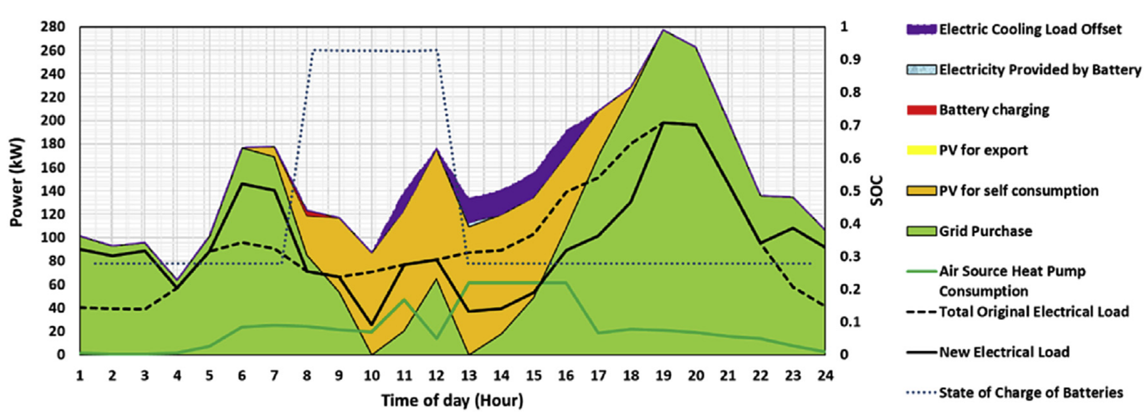
Scenario 8: June



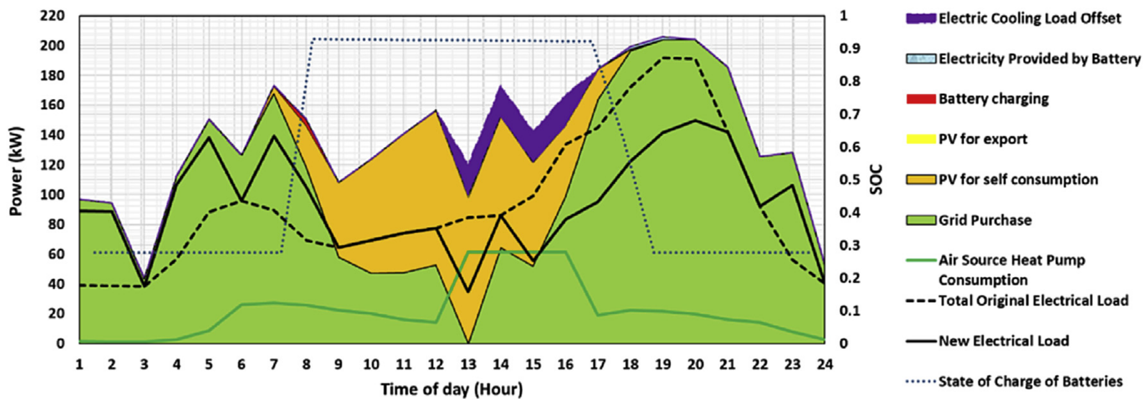
Scenario: August



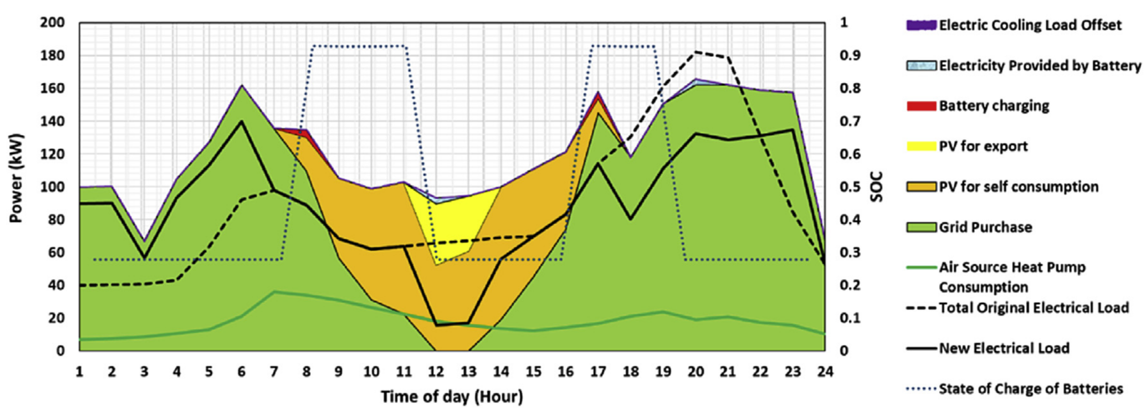
Scenario 8: September



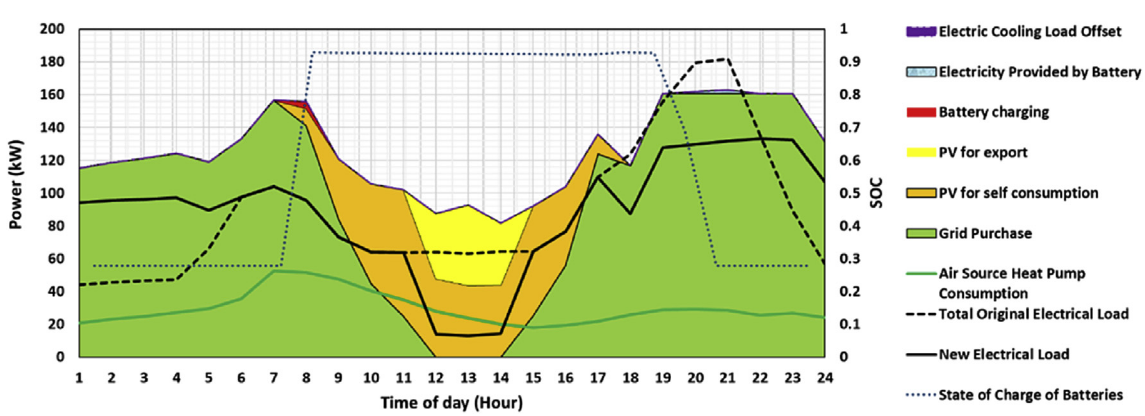
Scenario 8: October



Scenario 8: November



Scenario 8: December

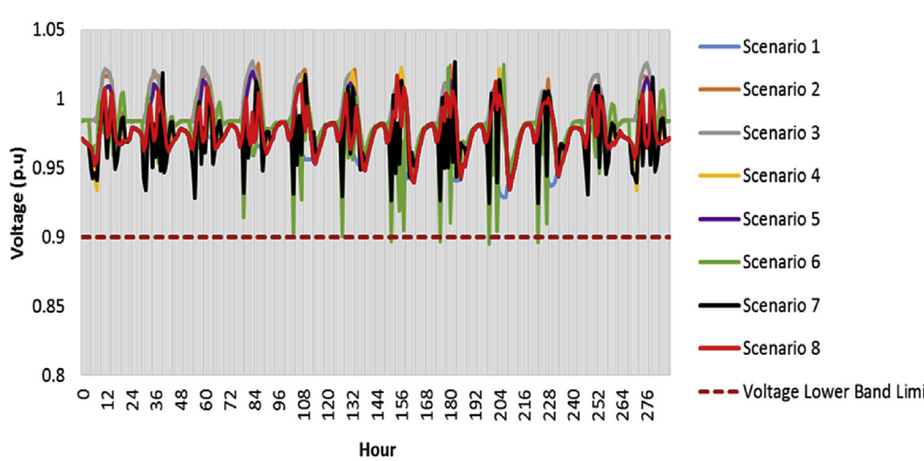


Appendix B

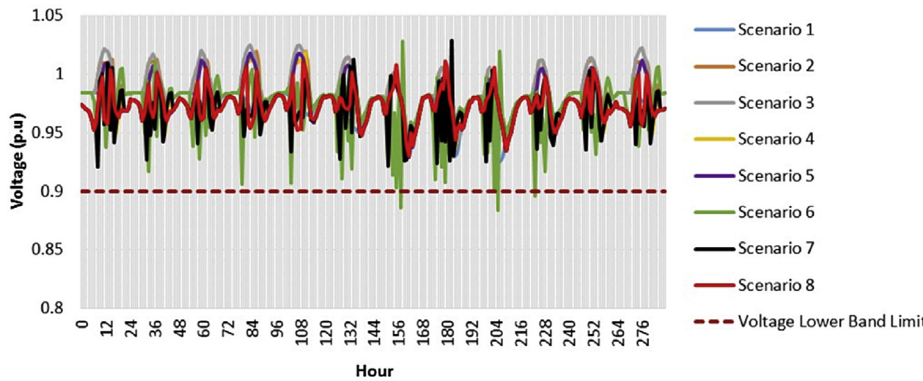
January	February	March	April	May	June	July	August	September	October	November	December
1	25	49	73	97	121	145	169	193	217	241	265
2	26	50	74	98	122	146	170	194	218	242	266
3	27	51	75	99	123	147	171	195	219	243	267
4	28	52	76	100	124	148	172	196	220	244	268
5	29	53	77	101	125	149	173	197	221	245	269
6	30	54	78	102	126	150	174	198	222	246	270
7	31	55	79	103	127	151	175	199	223	247	271
8	32	56	80	104	128	152	176	200	224	248	272
9	33	57	81	105	129	153	177	201	225	249	273
10	34	58	82	106	130	154	178	202	226	250	274
11	35	59	83	107	131	155	179	203	227	251	275
12	36	60	84	108	132	156	180	204	228	252	276
13	37	61	85	109	133	157	181	205	229	253	277
14	38	62	86	110	134	158	182	206	230	254	278
15	39	63	87	111	135	159	183	207	231	255	279
16	40	64	88	112	136	160	184	208	232	256	280
17	41	65	89	113	137	161	185	209	233	257	281
18	42	66	90	114	138	162	186	210	234	258	282
19	43	67	91	115	139	163	187	211	235	259	283
20	44	68	92	116	140	164	188	212	236	260	284
21	45	69	93	117	141	165	189	213	237	261	285
22	46	70	94	118	142	166	190	214	238	262	286
23	47	71	95	119	143	167	191	215	239	263	287
24	48	72	96	120	144	168	192	216	240	264	288

Appendix C

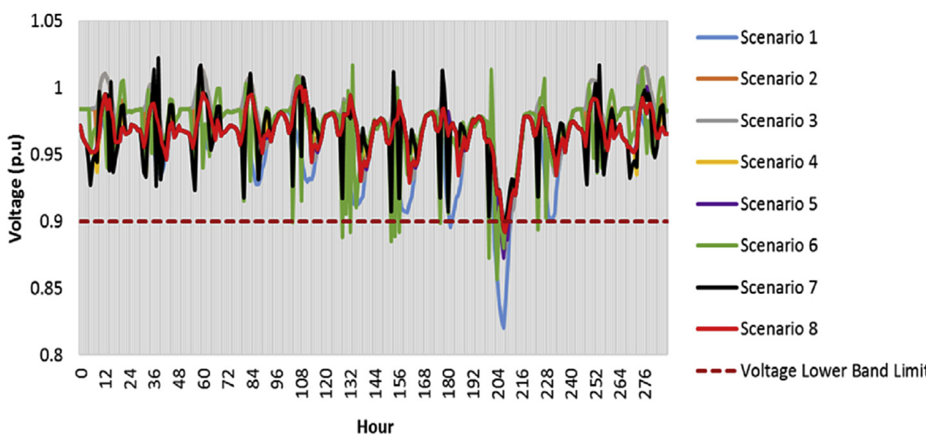
Weekdays



Peak Days



Weekend Days



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